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The Effect of Sensor Resolution on Detection of Vegetation in the City of Atlanta, Georgia in June 2011

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THE EFFECT OF SENSOR RESOLUTION ON DETECTION OF VEGETATION IN THE CITY OF ATLANTA, GEORGIA IN JUNE 2011

By

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ABSTRACT

INTRODUCTION: Identifying the amount of vegetation in small geographic plays an important role in understand the contribution of the built environment to Heat Stress Illness (HSI) in urban areas. Vegetation is often identified using remotely sensed satellite imagery, using the Normalized Difference Vegetation Index (NDVI). However, it is possible that small areas, such as census tracts or block groups, may be sensitive to the resolution of the sensor used for NDVI classification.

AIM: The aim of this study is to determine if the sensor resolution of remotely sensed data produces significantly different NDVI classifications for census tracts and block groups in the Atlanta area for 2011. In addition, we examined the role of landcover classification in understanding these differences.

METHODS: Using the 2010 geographic designations for census tracts (n=142) and block groups (n=358) in the Atlanta area, mean NDVI values were calculated and compared. The imagery used was from the Landsat5 (30m resolution) and QuickBird (2.44m) satellites taken in June 2011. Proportions of landcover classifications were calculated using the 2011 National Land Cover Database and compared to NDVI mean differences.

RESULTS: QuickBird classifications were significantly higher than the Landsat5 classifications at both the census tract and block group level (p value). We found correlation for NDVI difference with standard deviation of the high resolution NDVI values ($r(356)=-0.61$, $p<.0001$), Developed Medium Intensity landcover($r(356)=-0.59$, $p<0.0001$), Developed High Intensity landcover ($r(356)=-0.51$, $p<.0001$), and All Forest landcover ($r(356)=0.55$, $p<.0001$).

DISCUSSION: High-resolution imagery produced higher NDVI values for census tracts and block groups for the city of Atlanta in 2011. Our analysis suggests that High-resolution imagery may be beneficial in improving accuracy of identifying urban neighborhoods at higher risk of HSI.

APPROVAL PAGE

THE EFFECT OF SENSOR RESOLUTION ON 2011 VEGETATION DETECTION AT THE MICROSCALE LEVEL OF ATLANTA, GEORGIA

by

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Author's Statement Page

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Signature of Author

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Chapter I

Introduction

The average temperature of the Earth has been shown to be rising. Extreme weather events have also been occurring in increasing numbers. As the Earth's temperature continues to rise, extreme weather events will continue to occur more often and become more extreme (Meehl & Tebaldi, 2004). Extreme weather events that pose a high risk of negative health effects for humans are extreme heat events. Extreme heat events are defined as a temperature of an area is higher than average, or expected, for the same area. They are defined using a range of percentiles between 90-99, with above the 95th being the most common limit (Anderson & Bell, 2011). Extreme heat events can lead to an increase in heat stress illness (HSI) in humans. The CDC estimates that upwards of 600 people die per year in the United States of HSI (CDC). In 2003, the WHO estimated that 70,000 excess deaths occurred in Europe due to heat (Robine et al., 2008). This is notable due to deaths from HSI are largely preventable. Extreme heat events have been shown to be occur more frequent and intense in urban areas than rural areas, largely due to an effect known as the urban heat island (UHI) (Son, Lane, Lee, & Bell, 2016). Over half of the world's population lives in urban areas, with 66% of the world's population projected to live in urban areas by 2050 (Nations, 2014). While populations most at risk are older adults and young children, extreme temperatures can exacerbate strenuous activities performed by healthy adults (CDC). Heat stroke is the third most common cause of death for athletes, with neck and heart injuries being more prevalent (Noonan, Bancroft, Dines, & Bedi, 2012).

Urban environments have unique characteristics that effect their climate, raising temperatures relative to surrounding rural areas, but this effect may be inverse in desert areas. The main characteristic that drives this temperature difference is a large amount of impervious surface, and a low amount of vegetation. This leads to an effect known as the Urban Heat Island (UHI). Many cities show this effect, exhibiting temperatures 1-3℃ above surrounding areas (United States Environmental Protection Agency, 2018). UHI is thought to increase the effects, the intensity and frequency, of extreme weather like heat waves (Son et al., 2016). Several studies have shown that urban areas have higher rates of mortality than rural areas during heat events (Gabriel & Endlicher, 2011), along with intra-urban differences (Buyantuyev & Jianguo, 2010).

The spatial variation in land temperatures, especially dramatic in urban environments, can be attributed to factors such as land cover and tree canopy (Son et al., 2016). One measurement, Normalized Difference Vegetation Index (NDVI) has been shown to be a proxy of land surface temperature measurement (Weng, Lu, & Schubring, 2004). NDVI is a measurement of the amount of vegetation in an area, calculated using different wavelengths of light obtained through multispectral remote sensors on satellites. The resolution of the satellite sensors can vary from large 30m to smaller <3m. However, this resolution may impact the size of an area that NDVI can be calculated for. Higher resolution private satellites may be able to produce a higher resolution NDVI map. However, it is unclear whether the cost to use these private data sources is important to understand the possible impact on temperature in dense urban settings. The goal of this paper is to compare the mean NDVI at census tract and block group level produced by two sensors – Landsat5 (low-resolution) and QuickBird (high-resolution) satellites to determine if the NDVI produced is different and examine reasons for that difference.

Chapter II

Literature Review

Heat Stress Illnesses Burden

According to National Oceanic and Atmospheric Administration's (NOAA) National Weather Service data, heat is the cause of more deaths in the United States than any other weather-related cause (Jagai, Grossman, Navon, Sambanis, & Dorevitch, 2017). Additionally, Heat Stress Illnesses (HSI) are responsible for many nonfatal injuries, with heat being the largest cause of environmental injuries for emergency department visits between 2001-2004 (Sanchez, Thomas, Malilay, & Annest, 2010). During the months of May through September for the years 2005-2010, emergency departments in the US reported 98,462 admissions due to HSI as the primary reason for admission, with a crude incidence rate of 32.2 cases per 100,000 persons (Fechter-Leggett, Ambarish, & Ekta, 2016). As the earth's temperature continues to increase, it is expected that HSI will continue to increase as well. Increased temperature also has a positive association with death and illness from infectious diseases and air pollution (Harlan, Brazel, Prashad, Stefanov, & Larsen, 2006).

All persons are at risk for HSI, but certain subgroups have been identified to be more at risk than others. Older adults, young children, and those living with respiratory or cardiovascular conditions have been found to have increased risk (Basu, 2009). Other risk factors include participating in outdoor activities for all persons, while elderly people are at increased risk even while remaining in their home (Yip et al., 2008) or nursing care facility (Hajat, Kovats, & Lachowycz, 2007). Low income and minority residents also face an increased risk compared to their neighbors (Harlan et al., 2006). Neighborhood characteristics for these populations are associated with low amount of open space and vegetation, and a lack of coping resources like social resources and air conditions for homes (Harlan et al., 2006).

Urban areas experience heat waves more often than rural areas (Zhou, Rybski, & Kropp, 2017), mostly attributed to the urban heat island effect (UHI). UHI has been shown to increase the risk of HSI in urban areas compared to neighboring rural areas (Jagai et al., 2017). Amongst urban areas, some characteristics that can lead to a higher risk of HSI include a mild summer climate, leading to less air conditioner use in the population, and having a higher population density (Medina-Ramón & Schwartz, 2007). Lower income or elderly residents may not have sufficient resources to cool their homes comfortably (Harlan et al., 2006), increasing their risk of HSI outcomes that are otherwise preventable.

In a study of 43 US cities between 1987-2005, daily mortality rates were estimated to be 3.7% higher during heat wave days compared to non-heat wave days (Anderson & Bell, 2011). For the years 1993 to 2012, the most common reasons for emergency department visits during extreme heat days in the Atlanta area were acute renal failure and stroke (Tianqi, Sarnat, Grundstein, Winquist, & Chang, 2017). Kidney diseases have been identified as one of the most common reasons for hospitalizations during heat waves in Illinois between 1987-2014 (Jagai et al., 2017). While some decrease in mortality and high temperature has been detected, this may be due to adaptation and mitigation, and health risks still exist.

There is some difficulty in measuring the true burden of HSI due to a lack of standard definition for extreme weather events. Heat waves, for example, have no consistent definition. Definitions vary from using only an air temperature threshold, an air temperature threshold for a specified duration, and sometimes include requirements for humidity (Koppe, Kovats, Jendritzky, & Menne, 2004). There is even discrepancy on the temperature threshold to use, with percentiles ranging from 90 up to 99. An evaluation conducted by Cheng et al. (2018) used 15 different definitions for heatwaves. This lack of definition leads to two problems. One, epidemiologic studies must take the variance in definitions into consideration when calculating HSI outcome rates. Two, it makes it more difficult to create best practice guidelines for intervention and mitigation purposes. There is also evidence that heat waves can have different effects on health, with spring-time heat waves having a larger effect than summer heat waves (Hajat, Kovats, Atkinson, & Haines, 2002).

NDVI as a Proxy for Land Surface Temperature and its Use in Urban Areas

Land surface temperatures (LST) is one of the strongest predictors of heat stress risk (Dugord, Lauf, Schuster, & Kleinschmit, 2014), (Kestens et al., 2011). However, temperature sensors and weather stations have a limited effective radius, leading to an incomplete network of temperature data for continuous areas. Studies have shown that the UHI effect is not homogenous for cities, with intracity temperature differences being associated with urban and socioeconomic factors including greener landscapes (Son et al., 2016). This need for temperature data for areas not located near weather stations has led to the development and use of remote sensing data to identify temperature variation. Satellites such as the LANDSAT and MODIS collect thermal and other wavelengths which can be used to create temperature maps for any area (Kestens et al., 2011). Normalized Difference Vegetation Index (NDVI) maps can also be used as a proxy for thermal maps. NDVI maps show the amount of vegetation of an area, using a scale of -1 to +1. Negative values typically represent water features. Low but positive values (<.1) represent impervious surfaces or clay, both poor at mitigating heat. Higher positive values represent grass or trees (NASA). The validity of vegetation as a LST estimator is extensive (Weng, Lu, & Schubring, 2004). Vegetation can reduce the nearby air temperature in a number of ways, including direct shade and through evapotranspiration (Kurn, Bretz, Huang, & Akbari, 1994).

In an urban environment, vegetation has been identified as an effective way to reduce urban temperatures, reducing the UHI effect and reducing HSI (Solecki et al., 2005; Susca et al., 2011). Economically, increasing vegetation in urban areas can reduce cooling costs by almost double the cost of planting a tree (Koppe et al., 2004). Some studies have examined other methods of attempting to mitigate HSI risk by reducing the UHI effect, generally by the methods of increasing albedo, by using more reflective materials for roofs or roads (Hudischewskyj, Douglas, & Lundgren, 2001), and by increasing vegetation as recommended by the EPA ("Heat Island Cooling Strategies,"). Vegetation has been shown to have the greatest effect on reducing the radiant temperature of an area, which has the largest effect on heat sensation (Jendritzky, Staiger, Bucher, Graetz, & Laschewski, 2000).

Need for Microscale Measures

With the high burden of disease from HSI and the expectation that extreme heat events will becoming increasingly frequent, there is a need for accessible and accurate measure for assessing communities with elevated risk for HSI. Research on risk assessment at the micro-scale is sparse. Methods do exist for larger spatial areas, such as the Parallel Climate Model (Meehl & Tebaldi, 2004), a model with a resolution on the scale of 2.8 degrees of longitude and latitude for land. While this may be helpful for characterizing regions, it lacks the granular ability to be useful for identifying trends below the county level.

Other risk assessment plans focus on temporal aspects, forecasting extreme temperatures to warn the target area's population of an upcoming event. These systems are generally limited to larger geographic areas, cities and regions (Koppe et al., 2004), and interventions are limited to behavior changes (CDC). These systems also are only forecasted days in advance, leaving little time for intervention strategies beyond the described individual actions. There is also limited research with how effective these forecasts and interventions are. An evaluation conducted by Nitschke et al. (2016) looked at health outcomes and mortality in Adelaide, South Australia between a heat wave in 2009, which sparked the city to develop a warning system, and two similar heat waves in 2014. They detected a significant decrease in health outcomes for cardiac, renal, and heat-related emergency visits and ambulance calls, with an increase in excess deaths from 34.5 to 38.2.

The difference of using high-resolution remotely sensed images to produce NDVI images, compared to low or moderate resolution images, has not been well explored. A comparison of high-resolution (0.6m) land cover data and low-resolution (30m) NDVI data was done by Li, Saphores, and Gillespie (2015). While using two different measures, they found that the low-resolution NDVI imagery was not as effective as the high-resolution data at detecting fine tree canopies and grasses. The authors hypothesized that the 30m resolution of the NDVI data was too coarse for most urban trees, typically in the form of streetscaping, or smaller areas of grass. Munyati and Mboweni (2013) found a similar effect between 10m, 250m, and 1km resolutions when looking at savanna vegetation in South Africa. Up to a 28% decrease in NDVI values was found for areas with a low magnitude of vegetation.

With an effective way to characterize their city on a level such as census tract or block group, more targeted interventions can be enacted. Census tracts are designed by the US Census Bureau to contain about 4,000 people, with block groups containing between 600 and 3,000 persons (Geography, 2012). For cities that may have a population into the millions, being able to target neighborhoods more at risk for HSI would allow for a more effective use of intervention and mitigation resources. As urban populations are expected to continue to increase, local governments would also benefit from a decrease in energy consumption. Intervention strategies could include the increase vegetation and building codes. Green roofs have been shown to be effective and reducing heat flux for individual structures in both the summer and winter months, as well as contributing to reducing the surrounding area's albedo (Susca et al., 2011).

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Chapter III

Manuscript

Introduction

Climate change is a recognized phenomenon occurring at present time (Gabriele C. Hegerl, 2007). One aspect of climate change is an increase in air temperature, leading to an increase in extreme heat events. Extreme heat events cause an average of 688 deaths per year in the United States (*A Human health perspective on climate change: a report outlining the research needs on the human health effects of climate change*, 2010). Extreme heat events are not only becoming more frequent but are also becoming more extreme. Extreme heat events are defined by temperatures higher than average for a given area (CDC), which leads to spatial and temporal variance between areas depending on each area's natural climate. One of the determinants of an area's frequency and duration of extreme heat events and risk of heat-stress illness (HSI) is vegetative land cover. Vegetation functions in reducing land temperature by providing shade and evapotranspiration (Jenerette et al., 2016). Vegetation can potentially reduce an area's temperature by 3 degrees Celsius (Kurn, Bretz, Huang, & Akbari, 1994).

Urban areas are more likely to overall have less vegetative cover and more impervious surface, therefore increasing the area's risk for heat stress illness (HSI) (*A Human health perspective on climate change: a report outlining the research needs on the human health effects of climate change*, 2010). This effect is commonly referred to as the urban heat island (UHI) effect. The effect occurs due to urban areas typically having a low albedo, or reflectivity, which can raise temperatures by up to 5 degrees Celsius compared to surrounding rural areas (O'Neill et al., 2009). However, urban areas are not uniform in their distribution of vegetative cover, impervious surface, and other environmental factors that play into risk for heat-related illness. Cities are also not uniform in distribution of socio-demographic factors (Luber & McGeehin, 2008). This leads to cities having areas of citizens that may be more at risk to heat illnesses than others and may be at risk of being misidentified. Chuang and Gober (2015) identified that using a national heat vulnerability index (HVI) led to misclassifications of census tracts in Phoenix, AZ on two ends, a high incidence of HSI hospitalizations for the years 2004-2005 predicted to have low incidence, and census tracts predicted to have high incidence that had zero incidence during the same period. The low predicted incidence neighborhoods tended to be wealthy areas near the city limits, and high predicted incidence neighborhoods were near the city center, low-income, with a higher average population of Hispanic residents and residents with diabetes.

The nationally applicable HVI used for mapping populations consists of socioeconomic, geographic, and health variables at the census tract level (Reid et al., 2009). They include information on poverty, education, race, and age, along with home characteristics of air conditioning and living alone. The variable of vegetation can be measured in land cover classifications or through a Normalized Difference Vegetation Index (NDVI) using remotely sensed images. With either method, areas low amounts of vegetations are associated with higher outcomes of HSI in urban areas (Chuang & Gober, 2015; Reid et al., 2009). The temporal and spatial resolution of the methods can vary. While high sensor resolution has been shown to be more accurate for mapping vegetation in non-urban areas (Valderrama-Landeros, Flores-de-Santiago, Kovacs, & Flores-Verdugo, 2017) and for economic purposes (Li, Saphores, & Gillespie, 2015), no research has been identified comparing using different sensor resolutions in urban areas for vegetation identification.

Currently, vulnerability mapping is mostly limited to using satellite imagery collected with low resolution sensors, typically from the Landsat program, resulting in a county-level scale. This may provide an incomplete picture for identifying these potential more vulnerable neighborhoods previously mentioned. Few research studies have used high-resolution data (Sawaya, Olmanson, Heinert, Brezonik, & Bauer, 2003). High-resolution data is not typically used due to cost and lack of availability, and the relationship between NDVI and image resolution is not well studied (Weng, Lu, & Schubring, 2004), especially at high resolutions. It is agreed that using low resolutions to measure temperature and vegetation in small geographic areas leads to inaccuracy (Nichol, 1994).

Because of the irregular nature of urban areas and the limitations of publicly available satellite imagery, a classification that applies to an entire county is not fine enough in scale to assess the actual vulnerability of an urban area. Atlanta is colloquially known as “The City in the Forest’ because of an estimated 2010 tree canopy of over 50% (Merry, Siry, Bettinger, & Bowker, 2014). Atlanta is the pilot city for this analysis both for its dense tree canopy, rapid population growth, and well-known urban sprawl (Stone Jr, Vargo, Peng, Yongtao, & Russell, 2013). The aim of this paper is to compare classifications of census tracts and block groups within the City of Atlanta in high (2m) and low-resolution (30m) scales, using the Normalized Difference Vegetation Index (NDVI), to determine if the high-resolution classification provides a meaningful difference for mean NDVI. In addition, we analyzed potential landcover classification associated with differences to better understand the role that enhanced NDVI resolution may have in vulnerability mapping. This will help add to the literature on the sensitivity of this indicator is to imagery resolution and if the resources for analyzing high resolution imagery are beneficial. This will also provide information on identifying hot-spots within city limits and where individual and communal interventions could be targeted.

Methods

Study Area

The area for the study was designated to be census tracks and block groups of the Atlanta area. TIGER/LINE Shapefiles for the area were obtained through the United States Census for boundaries from the year 2010. A total of 142 census tracts and 358 block groups that were within the city of Atlanta boundaries were included for this analysis.

Satellite and Land Cover Data

The low-resolution satellite image was obtained through the United States Geological Survey (USGS). USGS maintains public domain data through their Earth Resources Observation and Science Center. The image used for this study was taken with the Landsat 5 Satellite on June 15, 2011, a day with zero cloud cover. The sensor onboard, the Thematic Mapper, has a resolution of 30 meters for multispectral readings. The high-resolution Satellite imagery for the study area was purchased through DigitalGlobe, taken with the QuickBird Satellite, which collected multispectral imagery at a resolution of 2.44 meters. The date the image was taken is June 10, 2011 and had zero cloud cover.

Land cover data for the study area was obtained from the United States Geological Survey, using the 2011 National Land Cover Database, created by the Multi-Resolution Land

Characteristics Consortium. Aerial photographs for qualitative analysis were provided by GoogleEarth. The images were acquired on October 16, 2011.

Data analysis:

NDVI Classification

NDVI classifications of each resolution (census tract and block groups) were created using ERDAS Imagine, which uses the following standard NDVI formula:

NDVI = (Near Infrared Band – Red Band) / (Near Infrared Band + Red Band)

NDVI is used to determine how much vegetation is in an area. Healthy, lush vegetation absorbs more visible light and reflects more infrared light (NASA). The NDVI indicator analyzes this relationship for a given pixel in a raster image, and then produces a number between -1 and +1 for each pixel. Ranges of values are given for different types of surfaces, which exhibit different behavior reflectance and absorption of visible and infrared light. Typical values for vegetation in NDVI range from 0.81 for grass to 0.83 for confer and broadleaf forests. Impervious surfaces and soils have values closer to 0. For example, concrete returns 0.08, 0.14 for clay, and 0.15 for asphalt (Takeuchi & Yasuoka, 2004).

A mean NDVI value and standard deviation was then calculated for each of the 142 census tracts of the study area and 358 block groups for both resolutions using the zonal statistics tool. Additionally, a difference in means value was calculated using the following equation:

Mean NDVI Difference = High-Resolution Mean Difference – Low-Resolution Mean Difference

Higher Mean NDVI Difference values indicate a higher mean NDVI classification using the high-resolution satellite imagery.

Landcover classification:

To account for variations in the areas of block groups, the data was stratified by classification for each block group to obtain a count of how much land is in the area for each classification, then divided over the total count for the geographic unit to obtain the proportion of the block group covered by each land cover classification type. The block groups were then evaluated for the proportions of cover they contain for each land cover type found in the study area (14 of the 20 classifications). Descriptions of the types of land cover found in the study area are available in Table 1. Three aggregations of landcovers, Developed Open and Low, Developed Medium and High, and All Forests, were created. The definitions of the Developed group of land covers include criteria for impervious surface. Open and Low were grouped, representing less than 50% impervious surface. Medium and High were grouped, representing 50% or more impervious surface. All geographic analysis was performed using ArcGIS 10.14.

Table 1: Descriptions of Identified Landcover Classifications in Study Area

Class	Description
Water	Areas of open water, generally with less than 25% cover of vegetation or soil
Developed Open Space	Areas with a mixture of some constructed materials, but mostly vegetation in the form of lawn grasses. Impervious surfaces account for less than 20% of total cover. These areas most commonly include large-lot single-family housing units, parks, golf courses, and vegetation planted in developed settings for recreation, erosion control, or aesthetic purposes.
Developed Low Intensity	Areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 20% to 49% percent of total cover. These areas most commonly include single-family housing units.
Developed Medium Intensity	Areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 50% to 79% of the total cover. These areas most commonly

	include single-family housing units.
Developed High Intensity	Highly developed areas where people reside or work in high numbers. Examples include apartment complexes, row houses and commercial/industrial. Impervious surfaces account for 80% to 100% of the total cover.
Barren Land (Rock/Sand/Clay)	Areas of bedrock, desert pavement, scarps, talus, slides, volcanic material, glacial debris, sand dunes, strip mines, gravel pits and other accumulations of earthen material. Generally, vegetation accounts for less than 15% of total cover.
Deciduous Forest	Areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. More than 75% of the tree species shed foliage simultaneously in response to seasonal change.
Evergreen Forest	Areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. More than 75% of the tree species maintain their leaves all year. Canopy is never without green foliage.
Mixed Forest	Areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. Neither deciduous nor evergreen species are greater than 75% of total tree cover.
Shrub/Scrub	Areas dominated by shrubs; less than 5 meters tall with shrub canopy typically greater than 20% of total vegetation. This class includes true shrubs, young trees in an early successional stage or trees stunted from environmental conditions.
Grassland/Herbaceous	Areas dominated by gramanoid or herbaceous vegetation, generally greater than 80% of total vegetation. These areas are not subject to intensive management such as tilling, but can be utilized for grazing.
Pasture/Hay	Areas of grasses, legumes, or grass-legume mixtures planted for livestock grazing or the production of seed or hay crops, typically on a perennial cycle. Pasture/hay vegetation accounts for greater than 20% of total vegetation.
Woody Wetlands	Areas where forest or shrubland vegetation accounts for greater than 20% of vegetative cover and the soil or substrate is periodically saturated with or covered with water.
Emergent Herbaceous Wetlands	Areas where perennial herbaceous vegetation accounts for greater than 80% of vegetative cover and the soil or substrate is periodically saturated with or covered with water.

To examine differences between mean NDVI at census and block group levels, paired t-tests were conducted for each of the image resolutions and geographies, four in total. This was done to identify if the resolutions produced significantly different classifications for the census tracts and block groups. Scatter plots were generated, and Pearson correlation coefficients calculated to examine the relationship of the mean NDVI difference with the standard deviation of the high-resolution NDVI and each of the 14 land cover classifications for block groups. All statistical analysis was conducted using SAS 9.4.

A post-hoc qualitative analysis was decided on to provide some insight on the characteristics of block groups. Three block groups were selected based on their mean NDVI difference value from the lowest, highest, and median groupings, nine block groups in total. Aerial, high-resolution NDVI, and low-resolution NDVI images were referenced for visual purposes. Descriptive features of the block groups were based on their top three most common land cover classifications and apparent built features from the aerial images.

Results

At census tract level, we found statistically significant differences for high-resolution mean NDVI value minus the low-resolution mean NDVI value for census tracts (n=142), high-resolution classifications (M=0.55 SD=.135) were significantly higher than low-resolution classifications (M=0.47 Sd=0.12) t=43.02, p<.0001. As shown in Figure 1 and Figure 2, higher mean NDVI values were produced across the census tracts (and block groups) are produced from the higher resolution data with a spatial distribution suggesting X area has higher NDVI using the high resolution imagery. We found a similar statistically significant difference when examining NDVI at block group level: a mean NDVI of =0.58 SD=.13 compared to a mean NDVI of M=.49 SD=.12 using low resolution imagery, (Paired t-test, t=66.61, p<.0001). A paired t-test was conducted to determine the mean NDVI difference for the entire study area for each geographic region.

To determine major areas of difference between the sensors, we calculated the mean NDVI difference at the census tract and block group level comparing the higher resolution sensor to the low resolution sensor. The average difference between mean NDVI was 0.0869 (SD=0.0241) at the census tract level and 0.0886 (SD=0.0252) at the block group level. The high-resolutions standard deviations for each geographic classification were also analyzed.

In addition, to determine how variability NDVI score was using high resolution imagery we calculated the standard deviation of the NDVI over census tracts and block groups. Average standard deviation of the census tracts was 0.3538 and for block groups it was 0.3491. These results are summarized in Tables 2 and 3. Figures 3 and 4 show the values of the mean NDVI difference for each census tract and block group, respectively.

Table 2: NDVI Values of Study Area

Geographic Area	LR Mean NDVI			HR Mean NDVI			Mean NDVI Difference		
	Mean (SD)	t value	P-value	Mean (SD)	t value	P-value	Mean (SD)	t value	P-value
Census Tracts (n=142)	0.4679 (0.1197)	46.57	<.0001	0.5548 (0.1354)	48.82	<.0001	0.0869 (0.0241)	43.02	<.0001
Block Groups (n=358)	0.4915 (0.1169)	79.55	<.0001	0.5801 (0.1328)	82.65	<.0001	0.0886 (0.0252)	66.61	<.0001

Table 3: Standard Deviation of Mean NDVI Value for Study Area

Geographic Area	LR Standard Deviation			HR Standard Deviation		
	Mean (SD)	t value	P-value	Mean (SD)	t value	P-value
Census Tracts (n=142)	0.1687 (0.036)	55.72	<.0001	0.3538 (0.0344)	122.6	<.0001
Block Groups (n=358)	0.1573 (0.039)	76.34	<.0001	0.3491 (0.037)	178.5	<.0001

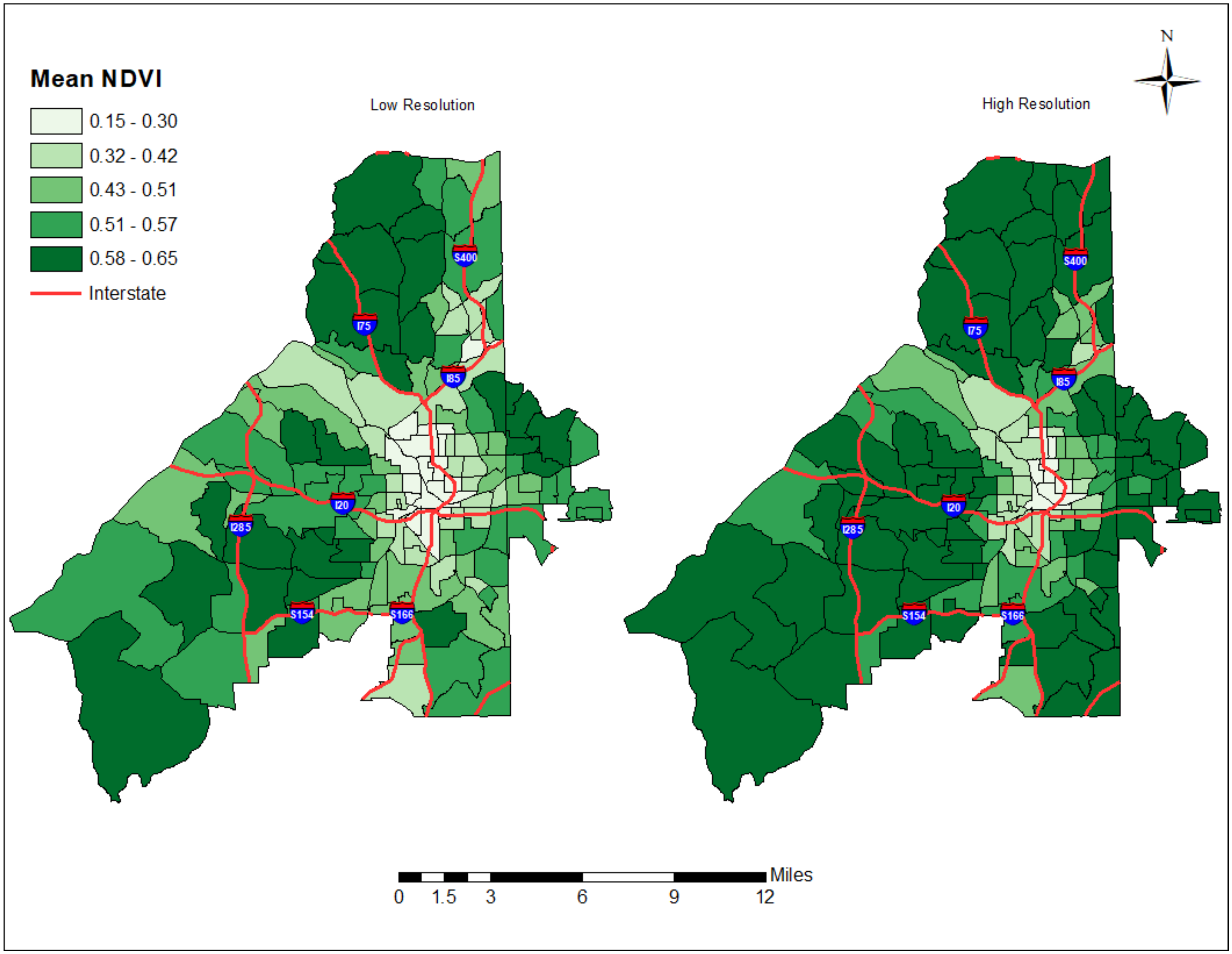

Figure 1: Low (left) and High (right) Resolution Mean NDVI values for Census Tracts

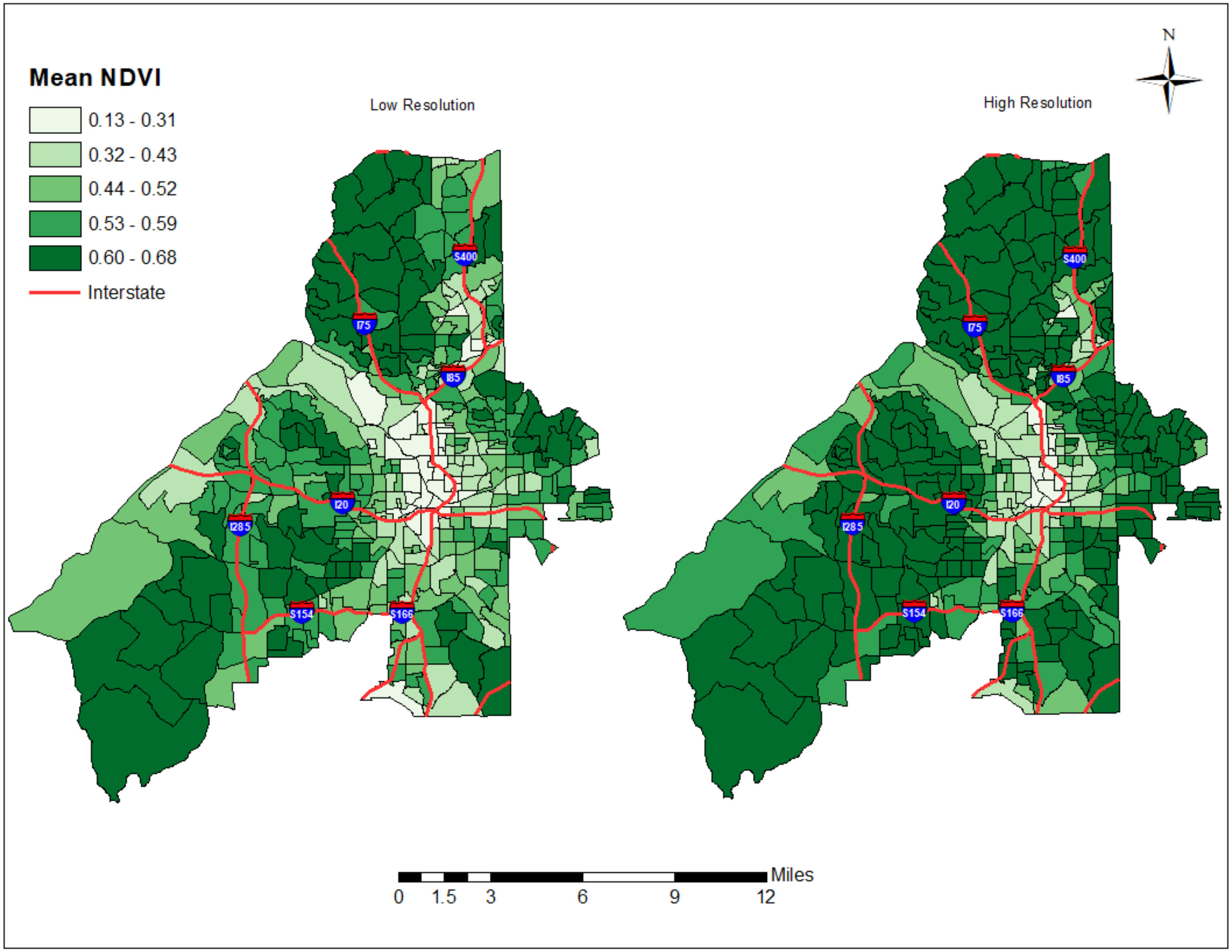

Figure 2: Low (left) and High (right) Resolution Mean NDVI Values for Block Groups

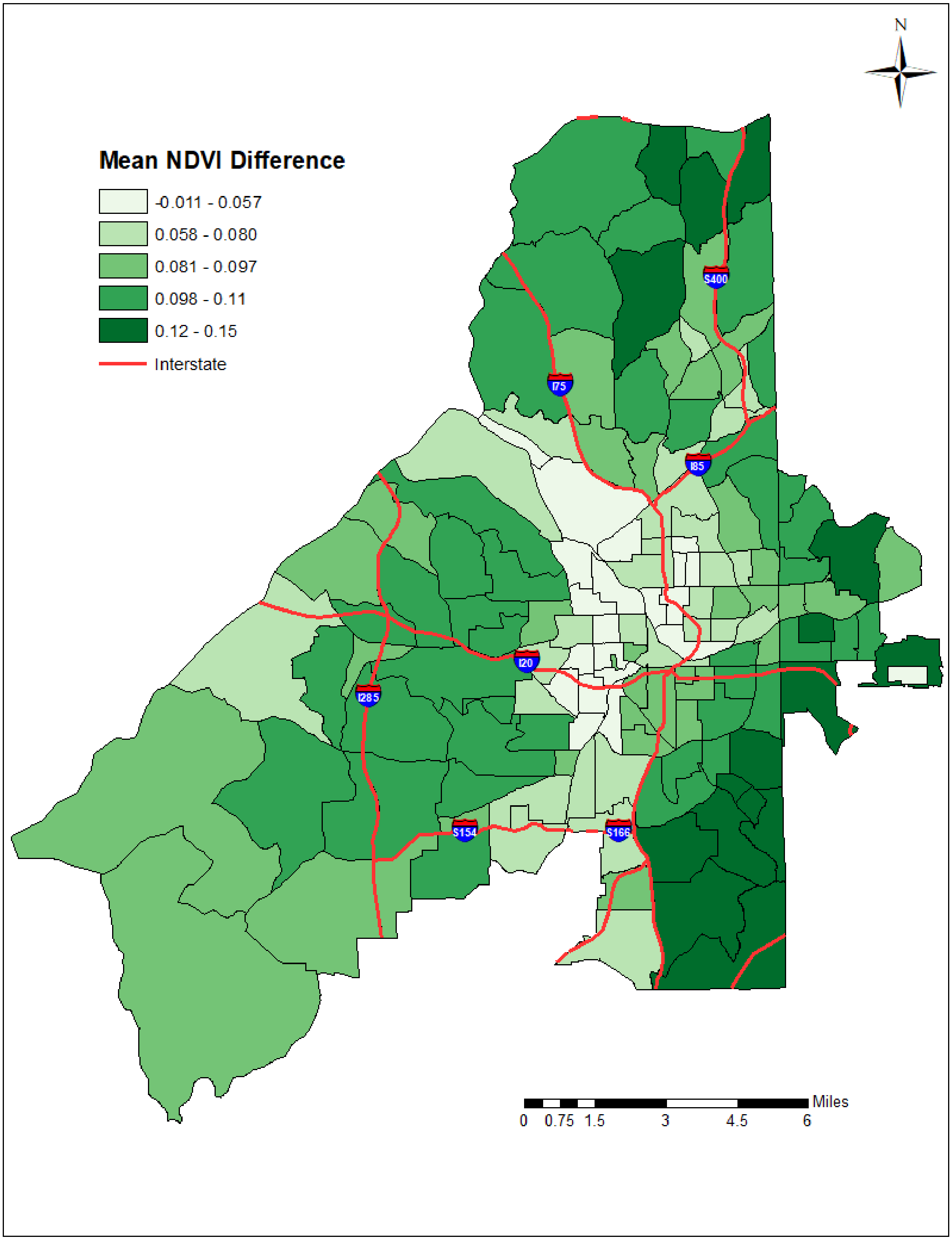

Figure 3: Mean NDVI Difference (high resolution – low resolution) for Census Tracts

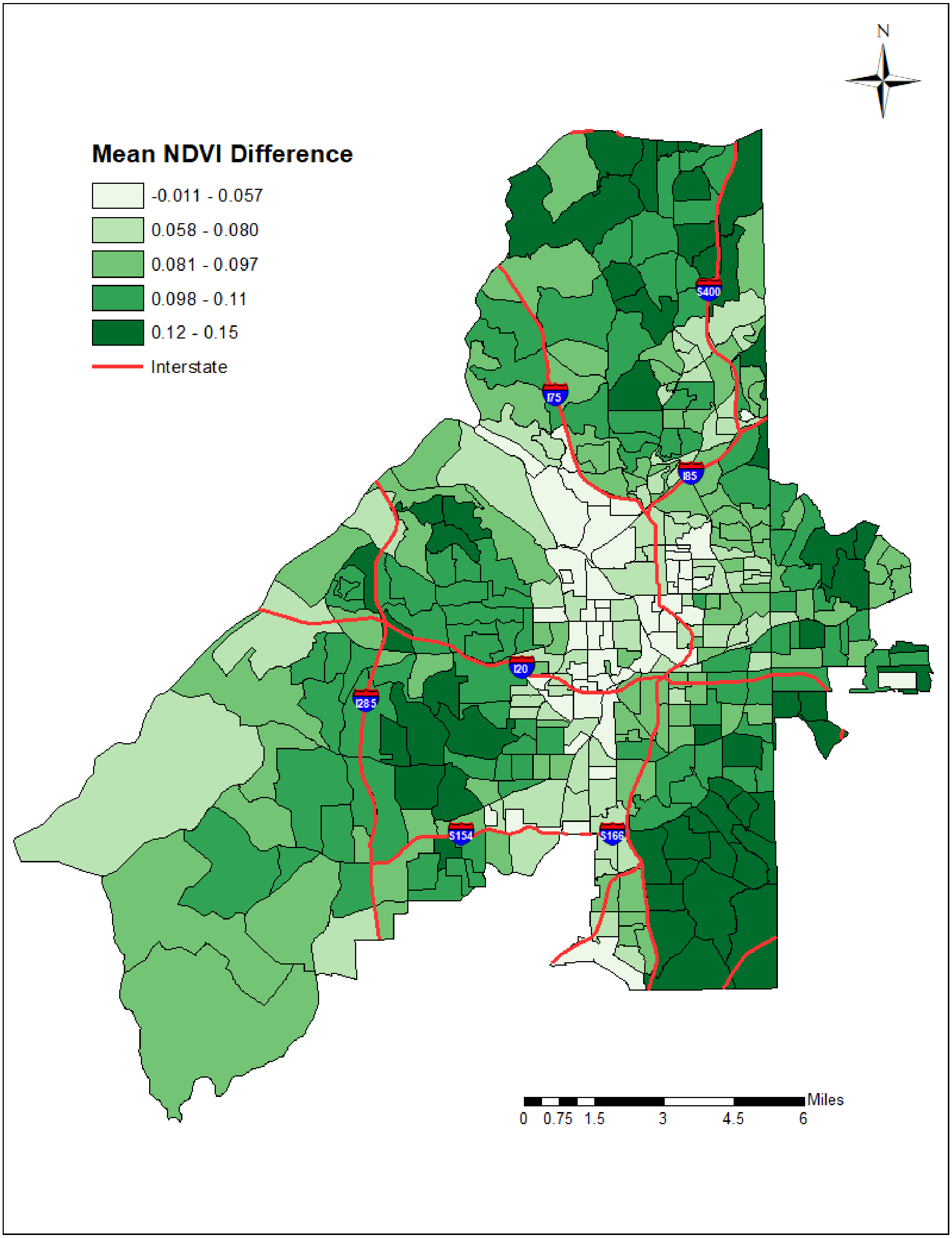

Figure 4: Mean NDVI Difference (high resolution - low resolution) for Block Groups

Qualitative Image Analysis

To examine the possible source of difference between the low resolution and high-resolution imagery, nine block groups were selected. The nine block groups consisted of three from the lowest, three from the median, and three from highest mean NDVI difference. Bright green represents high NDVI values. Dark red represents low NDVI values. All images are oriented with their north direction towards the top of the page.

Low Mean NDVI Difference

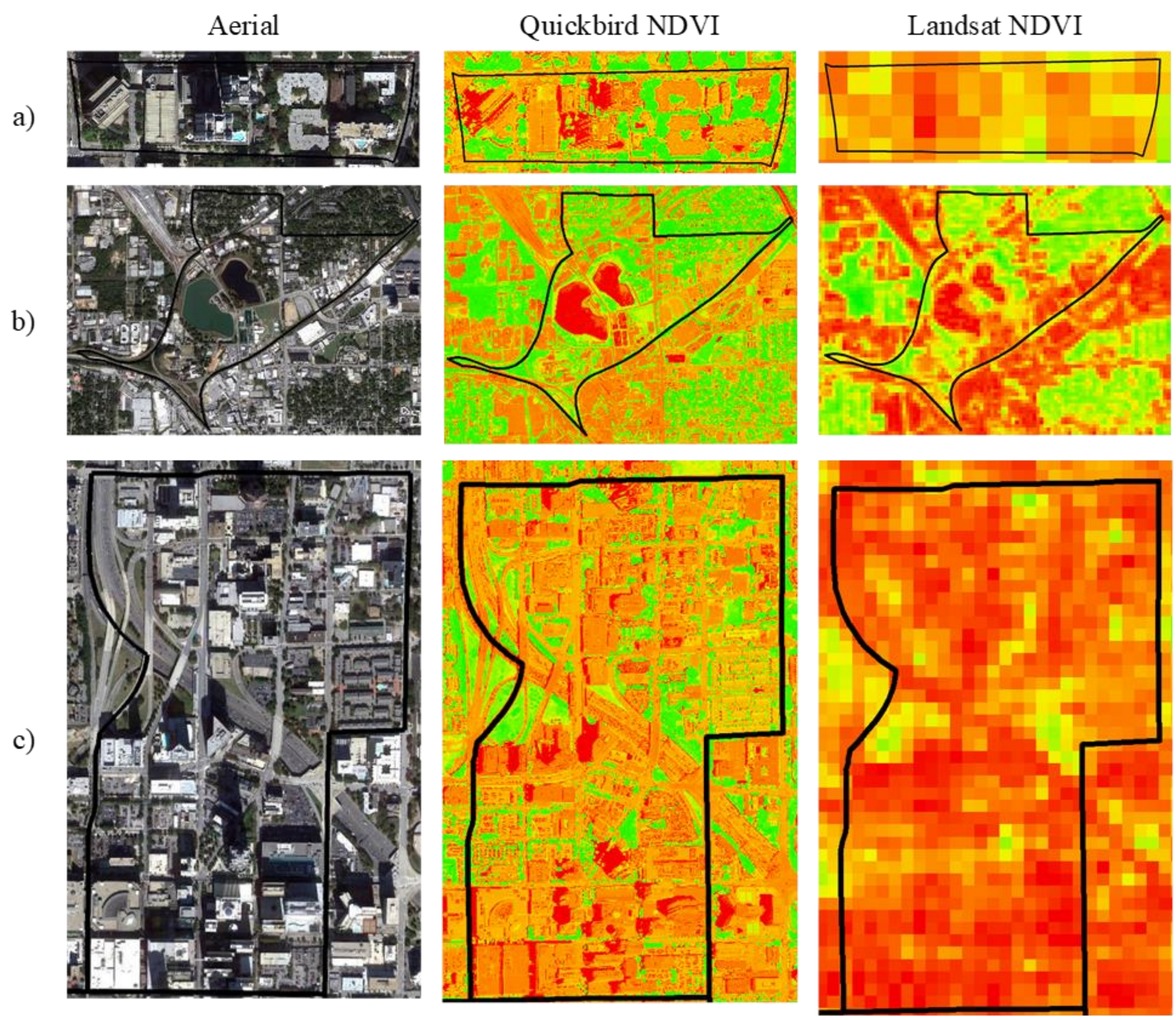

Figure 5: Low Mean NDVI Difference Block Group Imagery

The three lowest block groups with the lowest mean NDVI difference were all located near the center of the city. Of the most common land cover classification type , two had a high proportion of Developed High Intensity, and one had a high proportion of Developed Medium Intensity. The second and third most common land classifications types for these block groups were Developed Medium or Low Intensity, as shown in Table 4. The lone block group with a negative difference, where the high-resolution mean NDVI value was less than the low-resolution mean NDVI value, contains four high-rise office and condominium buildings, one of which appears to have a glass exterior. Roofing materials and the glass may lead to the disparity in mean NDVI value. It is also one of the smallest block groups in size. The second block group contains a large water treatment facility and some industrial retail space. The third block group is a large section of high rise buildings, including the tallest building in the city, a hospital, and several large hotels and office buildings. The city's main surface street, Peachtree Street, runs through the area, and is also intersected by the city's main interstate artery.

Table 4: Descriptive Statistics of Block Groups with Lowest Mean NDVI Difference Values

GeoID	Mean NDVI Difference	Standard Deviation	1st Landcover	2nd Landcover	3rd Landcover
a)131210011002	-0.01113	.4276	DevHI (45.61%)	DevMI (45.61%)	DevLI (8.77%)
b)131210089023	.00229	.42171	DevMI (30.99%)	DevLI (29.84%)	DevHI (15.99%)
c)131210019002	.01264	.36692	DevHI (72.73%)	DevMI (22.95%)	DevLI (5.31%)

Median Mean NDVI Difference

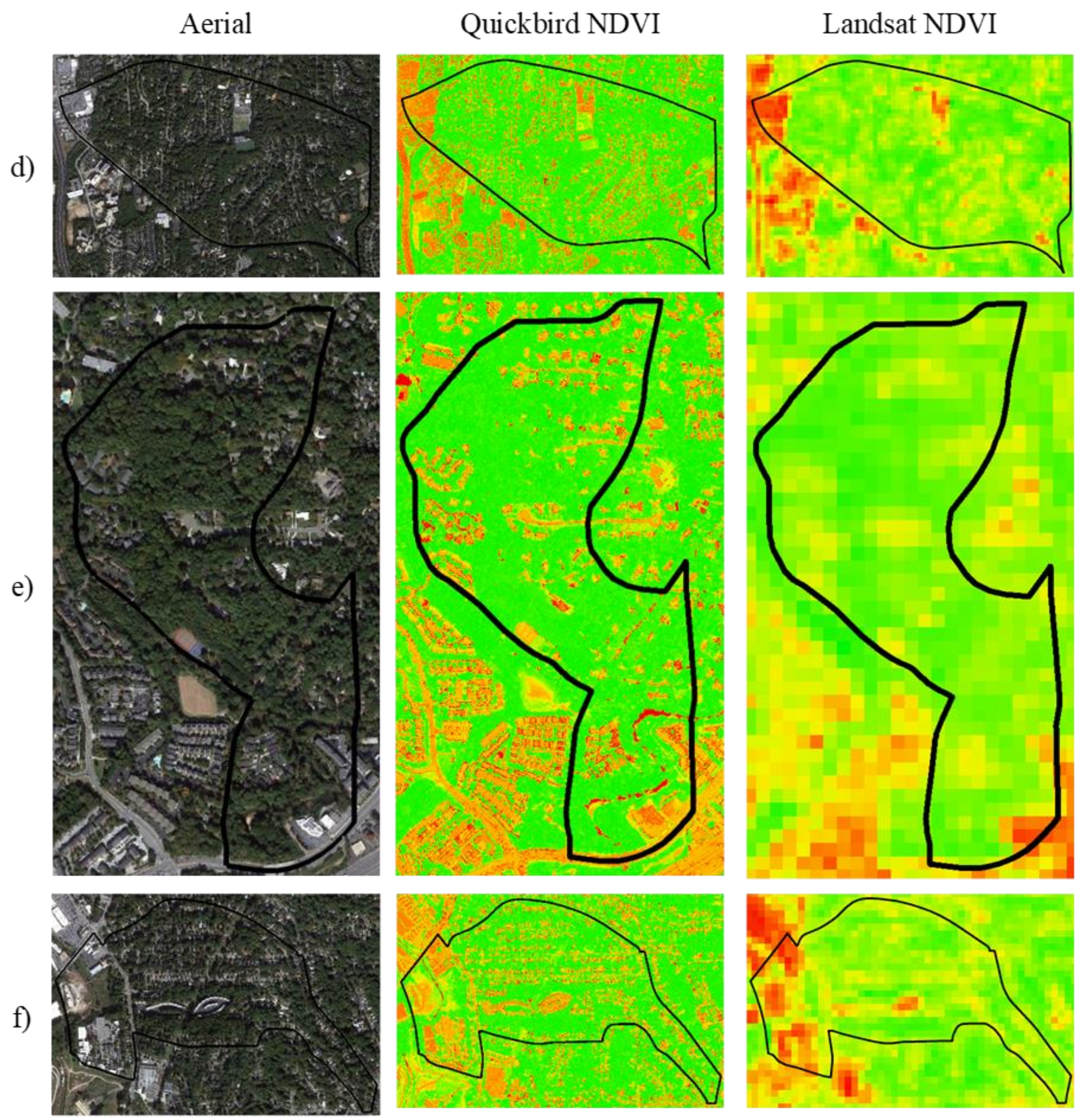

Figure 6: Median Mean NDVI Difference Block Group Imagery

The three block groups with the median mean NDVI difference values were located just north of the city center. The most common land cover in each block group was Developed Open Space, with two block groups having forest as their second most common land cover. The other classifications include developed low and medium intensity. Small condominium developments, parks, and single-family homes are the common characteristics of the group.

Table 5: Descriptive Statistics of Block Groups with Median Mean NDVI Difference Values

GeoID	Mean NDVI Difference	Standard Deviation	1st Landcover	2nd Landcover	3rd Landcover
d)131210098012	.09202	.32683	DevOp (43.50%)	Forest (34.93%)	DevLI (15.54%)
e)131210094043	09235	.34831`	DevOp (43.14%)	Forest (34.51%)	DevLI (21.20%)
f)131210002002	.09269	.36711	DevOp (37.02%)	DevLI (35.91%)	DevMI (11.19%)

High Mean NDVI Difference

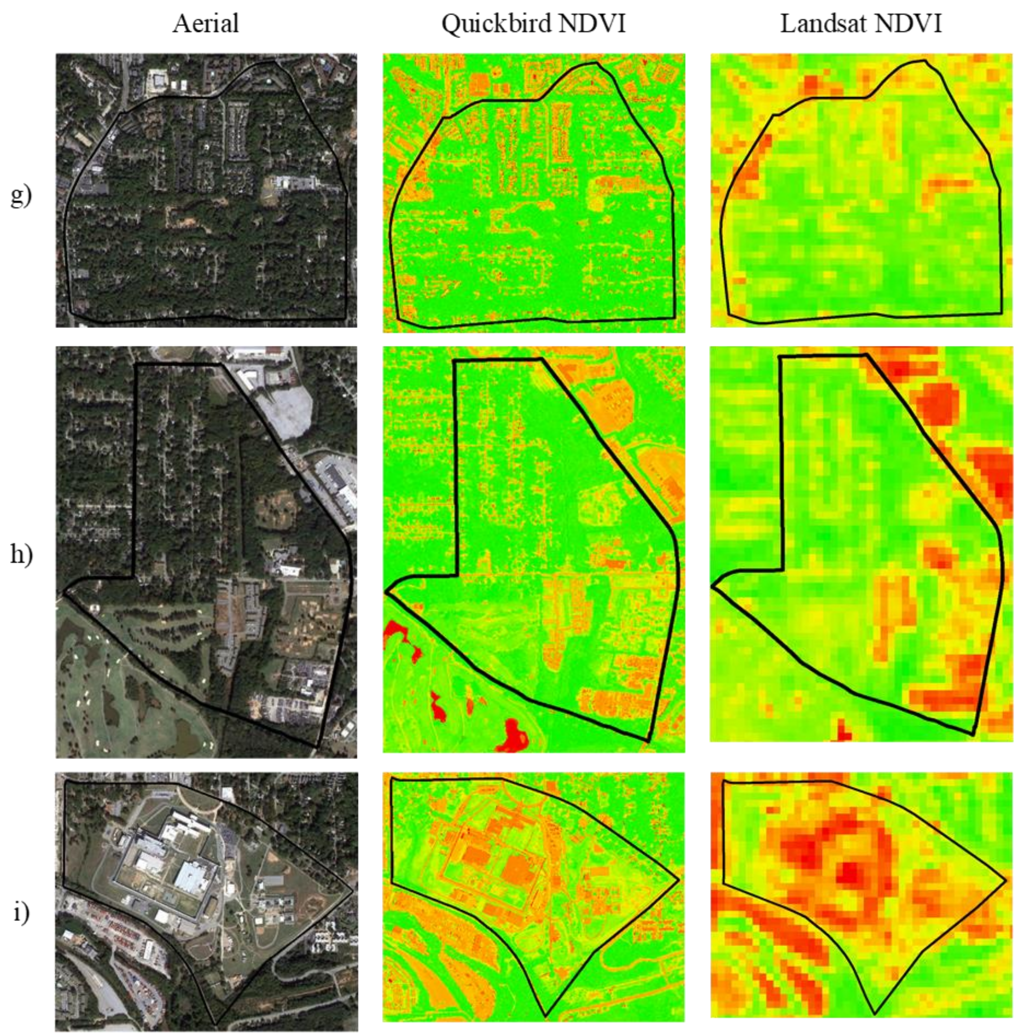

Figure 7: High Mean NDVI Difference Block Group Imagery

The three block groups with the highest mean NDVI difference were located on the northern and southern edges of the study area. Each block group has a different common land cover classification. All three share a presence of at least 30% developed open space. Single family homes, schools, townhomes, and a portion of a golf course are the shared characteristics of the second and third highest block group. The block group with the highest reported mean NDVI difference is dedicated to a federal prison.

Table 6: Descriptive Statistics of Block Groups with Highest Mean NDVI Difference Values

GeoID	Mean NDVI Difference	Standard Deviation	1st Landcover	2nd Landcover	3rd Landcover
g)131210101141	.13238	.32818	Forest (35.49%)	DevOp (32.97%)	DevLI (20.34%)
h)131210070021	.1389	.28608	DevOp (34.67%)	DevLI (27.28%)	Forest (22.88%)
i)131210068011	.14519	.29741	DevLI (34.24%)	DevOp (29.64%)	DevMI (21.79%)

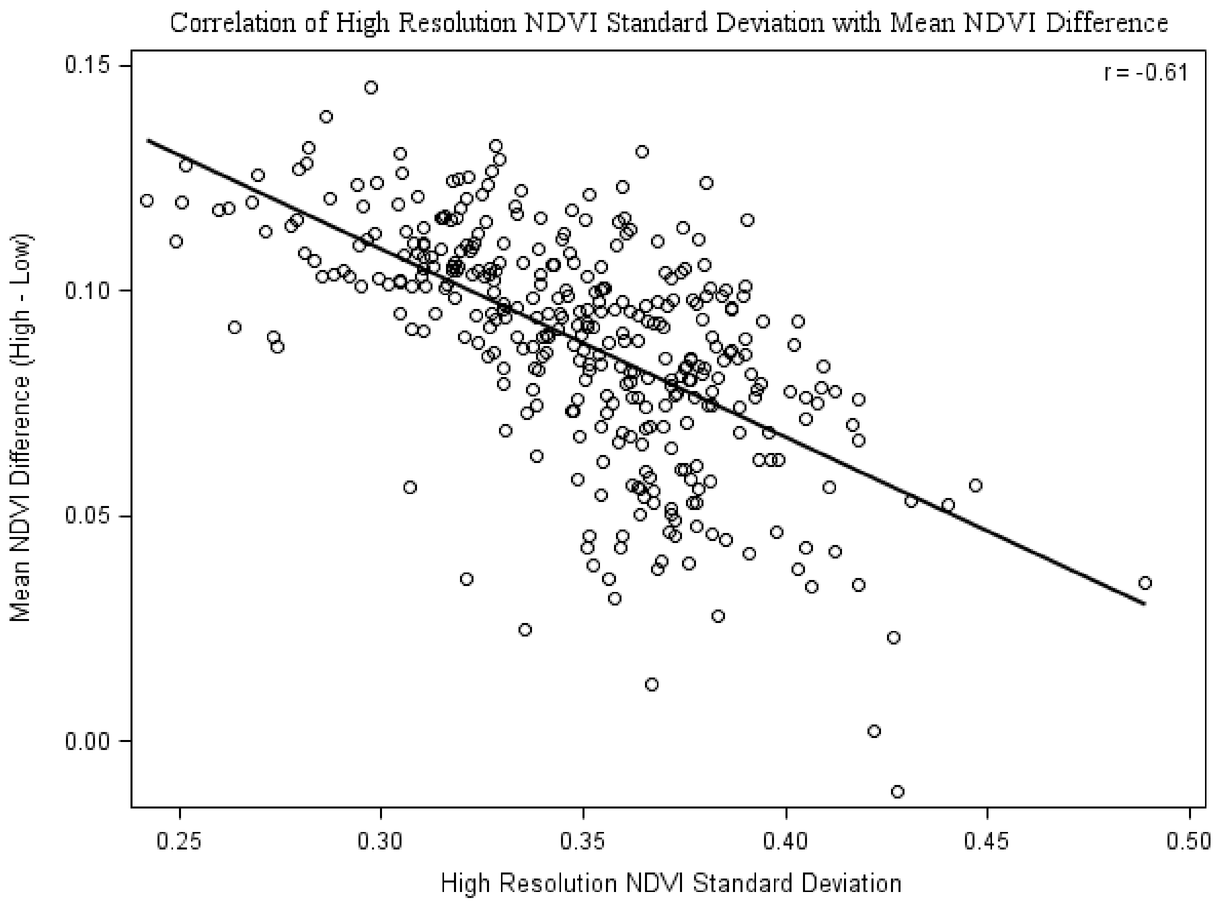

Figure 8: Correlation of High Resolution NDVI Standard Deviation with Mean NDVI Difference

To examine the impact of landcover classification and mean NDVI different, we calculated correlations between the NDVI Mean Difference value and the following: NDVI

Standard Deviation from high resolution imagery, and 14 Landcover classifications at the block group level. Three aggregations of landcovers, Developed Open and Low, Developed Medium and High, and All Forests, were also correlated. The definitions of the Developed group of land covers include criteria for impervious surface. Open and Low were grouped, representing less than 50% impervious surface. Medium and High were grouped, representing 50% or more impervious surface. The grouping of the three forest classifications was done with the belief that type of tree is not a factor in the tree's function in reducing UHI. As shown in table 7, we found significantly positive correlation with mean difference for the following: Significant correlations were found for all but three correlations (Table 7). Significant positive correlations were found for variables Developed Open Space ($r(356)=.47$, $p<.0001$), Developed Open+Low ($r(356)=.31$, $p<.0001$), Deciduous Forest ($r(356)=.45$, $p<.0001$), Evergreen Forest ($r(356)=.52$, $p<.0001$), Mixed Forest ($r(356)=.36$, $p<.0001$), All Forest ($r(356)=.55$, $p<.0001$), Grassland ($r(356)=.16$, $p=.0021$), Pasture/Hay ($r(356)=.11$, $p=.04$), Woody Wetland ($r(356)=.14$, $p=.0086$), and Emergent Woodland ($r(356)=.11$, $p=.0086$). Significant negative correlations were found for the variables High Resolution NDVI Standard Deviation ($r(356)=-0.61$, $p<.0001$), Water ($r(356)=-0.13$, $p=.0125$), Developed Medium Intensity ($r(356)=-0.55$, $p<.0001$), Developed High Intensity ($r(356)=-0.51$, $p<.0001$), and Developed Medium+High ($r(356)=-0.59$, $p<.0001$).

Table 7: Correlations with Block Group NDVI Mean Difference

Variable	r	P-value
High Resolution NDVI Standard Deviation	-0.61	<.0001*
Water	-0.13	0.0125*
Developed, Open Space	0.47	<.0001*
Developed, Low Intensity	-0.05	0.348
Developed Open+Low	0.31	<.0001*
Developed, Medium Intensity	-0.55	<.0001*
Developed, High Intensity	-0.51	<.0001*
Developed Medium+High	-0.59	<.0001*
Barren	-0.01	0.89

Deciduous Forest	0.45	<.0001*
Evergreen Forest	0.52	<.0001*
Mixed Forest	0.36	<.0001*
All Forest	0.55	<.0001*
Shrub	0.07	0.19
Grassland	0.16	0.0021*
Pasture/Hay	0.11	0.04*
Woody Wetland	0.14	0.0086*
Emergent Wetland	0.11	0.038*

Discussion

The high-resolution imagery produced a higher mean NDVI value in both the census tract and block group geographies than the low-resolution imagery. Overall, the high-resolution imagery was better at detecting vegetation, with the low-resolution tending to underestimate the amount of vegetation in the same geographic unit as expected (Jenerette et al., 2016). This effect was lessened when the geographic unit was more intensely developed or contained more water. Small vegetation, like grass and small bushes, contributed positively to the high-resolution NDVI classification but to a smaller degree than large trees.

The strongest correlate, shown in Figure 8, with the difference of mean NDVI block group values between the two sensor resolutions was the standard deviation of the high resolution NDVI. This is interpreted as more variance of NDVI in a block group made the two sensors more similar in detection ability. As NDVI is strictly a measure of light absorption and reflection, similar but not identical features are expected to return similar NDVI values. A higher variance in NDVI was interpreted as larger mix of features that return high and low NDVI values. Low NDVI values are associated with features such as impervious surfaces and clays. Landcover classifications that also contributed to the two sensor resolution classifications being more similar were water and developed areas. Areas with low, not tall, vegetation weakly contributed to a wider difference in sensor resolution.

The strongest correlates of landcover classification with a higher difference in mean NDVI block group values were the three standard forest classifications, the aggregated forest classification, and the Developed Open Space classification. Developed Open Space consists of managed grasses and deliberately planted vegetation and less than 20% impervious surface, which falls in line with expected results.

The result of the negative correlation of mean NDVI difference with the high resolution standard deviation value combined with the negative correlation of the developed classifications with higher rates of impervious surface may suggest that the low resolution NDVI classification is sufficient at classifying areas with low vegetation, or areas that may be at higher risk of HSI. Conversely, the positive correlations of lush vegetation with a higher mean NDVI difference leads to the conclusion that the low-resolution sensor may lead to an over classification of geographic units for high risk of HSI in environments with dense areas of vegetation, such as Atlanta, leading to a misappropriation of intervention resources. Johnson, Stanforth, Lulla, and Luber (2012) attempted to develop an environmental health index for Chicago, Illinois with data from the Chicago 1995 heat wave. The index used NDVI from Landsat5 data to classify block groups, similarly to the methods of this study. In their component analysis, the authors found that the component only accounted for 11.82% of variance from the index, and noted they expected much higher, almost double, influence from the variable. This lack of influence could be explained by using low-resolution data with small geographies. Census tracts and block groups alike are created to track populations, leading to a wide range in physical size of their boundaries. In higher population density areas, the size of these geographies decreases. The large pixels in low-resolution data may not fit perfectly into the census tracts and block groups, causing error in measurements. The high-resolution data has smaller pixels, which can fill in the small sized geographies better. However, large cities with a higher rate of impervious surface may be less affected by this effect and should be further researched.

One limitation of the study is the Landcover Classification data has a resolution of 30m, the same resolution as the low-resolution Landsat satellite data, and it is correlated with the high-resolution satellite data which is in 2.44m resolution. This may lead to some discrepancy in correlations. Currently, the only identified resource for landcover data in a similar high resolution is collected by NOAA's Coastal Change Analysis Program. The program produced classifications between 1-5m resolutions for select coastal regions of the United States. Sensor sensitivity is another factor that could lead to variations in future research. The two sensors used for the data in this study both have the same sensitivity for the NIR (760-900 nanometers) and red (630-690 nanometers) wavelengths used to calculate NDVI. Different sensors can have slightly different ranges for their data bands, leading to differences when comparing NDVI measurements for the same area (Soudani, François, le Maire, Le Dantec, & Dufrêne, 2006). Many land cover classifications were found to be significantly correlated with the mean NDVI value. Due to the number of statistical tests conducted, some results may be false positives. A condensed list of land cover classifications would help refine these correlations and reduce the risk of false positives. The effect of the non-forest vegetation classifications may be dispersed in the several classifications. Aggregating them together may show they have a stronger effect than found in this study.

The qualitative results illustrate a connection between the land cover classifications and the mean NDVI differences for block groups. The block groups with the lowest mean NDVI difference values are located near the city center and dominated by developed high and medium intensity cover, implying the two different sensor resolutions classify these land covers similarly. The lone block group with a negative value appears to contain a large glass building, which returns negative NDVI values. The block groups with median values of mean NDVI difference are located just outside the city center and dominated by developed open space and forest cover. The block groups with the highest mean NDVI values are located at the edges of the study area.

Each of the three has a different most dominant land cover of forest, developed open space, and developed low intensity. Perhaps the most interesting block group is the one with the highest mean NDVI difference, which is the site of a federal prison. It is a large grassy area with few trees and several stone buildings. The mean NDVI value for the zone may be misleading for urban health purposes. Grass is helpful in reducing UHI (Takebayashi & Moriyama, 2009), but its effect on reducing HSI risk is believed to be lower than trees (Harlan, Brazel, Prashad, Stefanov, & Larsen, 2006). However, communal risk for HSI is believed to be lowered by an increase open space and vegetation of any kind (Reid et al., 2009).

The effects of vegetation on reducing UHI and HSI risk are well documented. Specific to the Atlanta area, a survey conducted in 2013 showed that citizens of the city were willing to fund a project to increase the amount of trees in the city (Tran, Siry, Bowker, & Poudyal, 2017). The reasons reported by the respondents of the survey included cleaner air, heat reduction, aesthetics, and storm water control. Similar survey responses have been recorded in Tampa, Florida and Mandeville, Louisiana. The willingness to pay by citizens shows that the public recognizes the need for increased vegetation, and the results of this study should help city leaders collaborate with the public in constructive strategies to mitigate the UHI effect and potentially reduce HSI due to the increasing prevalence of extreme heat events. Future studies should examine urban health indexes with vegetation variables collected using different resolutions. The relationship of open and low intensity land covers on vegetation detection and their relationship to UHI should also be further explored.

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